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A review of computational optimisation methods applied to sustainable building design

Ralph Evins [a,b,c,d,*]

[a] Buro Happold, 17 Newman Street, London W1T 1PD, UK
[b] University of Bristol, Tyndall Avenue, Bristol BS8 1TH, UK
[c] EMPA, Swiss Federal Laboratories for Materials Science and Technology, Überlandstrasse 129, Dübendorf 8600, Switzerland
[d] Chair of Building Physics, Swiss Federal Institute of Technology ETH Zürich, ETH-Hönggerberg, Zürich 8093, Switzerland

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ABSTRACT

This paper presents a comprehensive review of all significant research applying computational optimisation to sustainable building design problems. A summary of common heuristic optimisation algorithms is given, covering direct search, evolutionary methods and other bio-inspired algorithms. The main summary table covers 74 works that focus on the application of these methods to different fields of sustainable building design. Key fields are reviewed in detail: envelope design, including constructions and form; configuration and control of building systems; renewable energy generation; and holistic optimisations of several areas simultaneously, with particular focus on residential and retrofit. Improvements to the way optimisation is applied are also covered, including platforms and frameworks, algorithmic comparisons and developments, use of meta-models and incorporation of uncertainty. Trends, including the rise of multi-objective optimisation, are analysed graphically. Likely future developments are discussed.

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* Correspondence address: EMPA, Swiss Federal Laboratories for Materials Science and Technology, Überlandstrasse 129, Dübendorf 8600, Switzerland.
Tel.: +41 58 765 6511.
E-mail address: ralph.evins@empa.ch

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1. Introduction

1.1. Sustainable building optimisation

Energy used in buildings for heating, cooling and lighting comprises up to 40% of the carbon emissions of developed countries [1]. Buildings are the sector with the greatest potential and lowest cost for carbon reductions [2]. There are many regulatory and certification incentives to make buildings more sustainable, including national building regulations, the EU Energy Performance of Buildings Directive (EPBD), BREEAM and LEED assessments and local planning policies. Computational simulation allows the energy used by proposed building designs to be quantified. This involves thermal, solar and air flow modelling and concerns the geometry, materials, control and systems of the building [3].

However, the design of sustainable buildings is not straightforward. All buildings are unique, and there are no prototypes. Designs must achieve high levels of performance for the lowest possible cost. There are many physical processes that lead to conflicting objectives. The design space of possible solutions is very large. These challenges have made it advantageous to apply computational methods of design optimisation.

1.2. This review

An initial search for relevant works was conducted using Google Scholar with search terms including ‘sustainable’, ‘energy’, ‘carbon’, ‘building’ and ‘optimisation’. Further searches were then conducted in the archives of the journals and conference proceedings identified. (Conference papers are included unless a similar journal paper exists, in which case it is given in preference). Papers cited by works found were also checked for relevance. From this broad search, articles were selected for inclusion in the main summary, Fig. 1, on the following basis:

- All areas of sustainable building design (e.g. water use) have been included in the search, although the works found are almost exclusively concerned with energy and carbon emissions.
- For technologies used in buildings, works have been included where there is significant information concerning building-level performance. For example, the design of an air conditioning system for a building is included, whereas the design of the coil within an air conditioning unit is not.
- Works must make significant use of computational optimisation. Works which use the term optimisation but perform only algebraic or manual processes (e.g. identifying the minimum via the low point on a graph) are not included, even if computational simulation is used to generate data.
- Works that focus on the optimisation process are not included in the summary (these are addressed separately in a later section).
- Works entirely concerned with dynamic control (including model-based control) are excluded, since this area is distinct from design optimisation, often having more in common with artificial intelligence.
- Only works since 1990 have been included. The final cut-off for inclusion was 1 October 2012.

In the first section of this paper, a brief overview is given for different methods of computational optimisation, including common algorithms. Next, works addressing major areas of sustainable building design are reviewed and discussed, covering: building envelope (including constructions and form); HVAC systems; renewable energy generation; and holistic appraisals that cover several areas. Each section discusses (for the single- and multi-objective cases) common formulations, novel approaches, and other works of interest not included in the main table. The final review section covers improvements to the optimisation process as applied to sustainable building design. The concluding section suggests possible future areas of profitable investigation based on current trends and omissions.

1.3. Previous reviews

Previous reviews have overlapped with elements of this field, though none have brought together all material related to optimisation and sustainable building design. An interesting early appraisal of optimisation and architecture is given in [4]. Gosselin et al. [5] reviewed the application of Genetic Algorithms (and briefly other methods) to heat transfer problems. Regarding energy generation, Baos et al. [6] covered the optimisation of renewable and sustainable energy and Pezzini et al. [7] reviewed optimisation techniques applied to power systems. The related field of multi-criteria decision analysis as an aid to sustainable decision-making was reviewed by Wang et al. [8]. There are numerous reviews of specific fields of building design including control [9], energy efficient design [10], passive design [11], and double-skin facades [12]. Reviews of urban-scale Combined Heat and Power (CHP) systems (i.e. not accounting for building-scale processes) have covered analytical optimisation [13] and economic dispatch optimisation [14]. In the wider area of engineering design optimisation, Roy et al. [15] reviewed methods and Marler and Arora [16] reviewed multi-objective methods.

2. Computational optimisation

2.1. Generic optimisation process

“Optimisation theory encompasses the quantitative study of optima and methods for finding them” - Beightler et al. in [17]. The following is a general mathematical description of the optimisation problem [18]:

Minimise $F(x_1,x_2,\dots,x_n)$

Ref	Author(s)	Date	MO	Topic		Optimisation Method	Objective(s)	Variables	Simulated system	Simulation Method	Program
[114]	Abdollahi & Meratizaman	2011	Y	Ren	N/A	GA (MOEA toolbox)	Exergetic efficiency, Cost rates	Plant capacities	CHP system	Steady-state	
[36]	Al Homoud	1997	N	Env	Comm	DS (Simplex; Nonlinear)	Energy	Constructions, Glazing	Envelope	Hourly (1 day/week)	EnerCalc
[37]	Al Homoud	2005	N	Env	N/A	DS (Nelder-Mead)	Energy	Constructions, Glazing	Envelope	Hourly (1 day/week)	EnerCalc
[38]	Al Homoud	2009	N	Env	Public	DS (Nelder-Mead)	Energy	Constructions, Glazing	Envelope	Hourly (1 day/week)	EnerCalc
[56]	Asadi et al	2012	Y	Env, Ren	Retrofit	DS (Tchebycheff)	Energy, Construction cost	Constructions, Glazing, Renewables	Envelope, Solar thermal	Degree-days	
[138]	Bichiou & Krarti	2011	N	Env, Sys, Cont	Resi	GA, PSO, Brute force	Life cycle cost	Shape, Constructions, Systems, Set points	Whole building	?	DOE-2
[35]	Bouchlagham & Letherman	1990	N	Env	Comm	DS (Simplex; Non-random complex)	Comfort	Constructions, Glazing, Shape	Envelope	Admittance method	
[82]	Caldas	2008	Y	Form	Comm	GA	Construction cost, Energy, Embodied energy	Layout, Shape, Constructions	Whole building	Annual hourly	DOE-2.1E
[70]	Caldas & Norford	2002	N	Form	Comm	GA	Energy	Window dimensions	Envelope	Daylight factor, ?	DOE-2.1E
[108]	Cassol et al	2011	Y	Lighting	Comm	Heuristic (GEO)	Lighting power, Lighting level	Light locations and powers	Lighting levels	Radiosity	
[148]	Chantrelle et al	2011	Y	Env, Cont	Retrofit	GA (NSGA-II)	Construction cost, Energy, Comfort	Controls, Constructions	Whole building	Annual hourly	TRN-SYS, COMIS
[103]	Chow et al	2002	N	Sys	N/A	GA	Operational cost	Supply and return flows and temperatures	HVAC system	Meta-model (ANN)	
[40]	Coley & Schukat	2002	N	Env	Community	GA	Energy	Constructions	Envelope	Lumped parameter (Annual hourly)	EXCALIBUR
[102]	Čongradac & Kulić	2012	N	Sys	N/A	GA	Energy	Chilled water temperatures	HVAC system	Meta-model (ANN)	EnergyPlus
[52]	Diakaki et al	2008	Y	Env	N/A	DS (Compromise; Goal)	Construction cost , Energy	Constructions	Envelope	Steady-state	
[113]	Evins et al	2011	Y	Ren	N/A	GA (NSGA-II)	Construction cost , Operational cost, Energy	Plant capacities, Construction dates	CHP system	Annual hourly	
[87]	Evins et al	2011	Y	Env	N/A	GA (NSGA-II)	Energy (heating; cooling)	Openings, Flow rate, Set points	Envelope	Hourly (typical weeks)	BCVTB, EnergyPlus
[140]	Evins et al	2012	Y	Env, Form, Sys, Ren	Resi	GA (NSGA-II)	Total cost, Energy	Shape, Constructions, Systems, Renewables	Whole building	Compliance methodology	SAP
[135]	Evins et al	2012	Y	Env, Form, Sys, Ren	N/A	GA (NSGA-II with local search)	Construction cost , Energy	Shape, Constructions, Systems, Renewables	Typical zone	Annual hourly	EnergyPlus
[56]	Fesanghary et al	2012	Y	Env	Resi	Harmony Search	Life cycle cost, CO2	Constructions	Whole building	Annual hourly	EnergyPlus
[100]	Fong et al	2006	N	Sys	N/A	Evolutionary Programming	Energy	Chilled water supply temp, Air supply temp	HVAC system	Monthly	TRN-SYS
[81]	Gagne & Andersen	2011	Y	Env	N/A	GA (micro-GA)	Daylight, Glare	Constructions, Shading	Envelope	Ray tracing	Lightsolve Viewer
[126]	Ghiaus & Jabbour	2012	WS	Ren	N/A	Design of Experiments	Construction cost , Operational cost	Collector area, Tank volume	Whole building	Monthly	TRN-SYS
[141]	Hamdy et al	2011	Y	Env, Form, Sys, Ren	Resi	GA (NSGA-II variant)	CO2, Construction cost	Constructions, Glazing, Systems	Whole building	Annual hourly	IDA ICE
[143]	Hamdy et al	2012	Y	Env, Form, Sys, Ren	Resi	GA (NSGA-II variant)	Energy, Life cycle cost	Constructions, Glazing, Systems, Renewables	Whole building	Annual hourly	IDA ICE, IDA ESBO
[49]	Hasan et al	2008	N	Env	Resi	PSO-HJ	Life cycle cost	Constructions	Envelope	Annual hourly	IDA ICE
[44]	Holst	2003	WS	Env	N/A	DS (HJ)	Energy , Comfort	Constructions, Glazing	Envelope	Annual hourly	EnergyPlus
[57]	Huang et al	2012	Y	Env	Resi	GA (Simple)	Humidity, Construction cost	Humidity buffer material location and thickness	Humidity level	Contribution Ratios	
[149]	Jin & Overend	2012	Y	Env, Sys	Retrofit	GA (NSGA-II)	CO2, Total cost, Comfort	Renovation strateges, Constructions	Whole building	Annual hourly	EnergyPlus
[48]	Kämpf & Robinson	2009	N	Env	Resi	CMA-EA, HDE	Energy	Constructions	Urban area	Ray tracing	CitySim
[77]	Kämpf & Robinson	2009	N	Form	Resi	CMA-EA, HDE	Energy	Shape	Urban area	Ray tracing	Radiance (PPF)
[80]	Kämpf et al	2010	Y	Form	N/A	Evolutionary algorithm (MOO)	Area, Solar	Shape	Urban area	Ray tracing	Radiance
[112]	Kayo & Ooka	2009	Y	Ren	N/A	GA	Energy, Total cost	Plant capacities	CHP system	Hourly (3 design days)	
[101]	Lee & Cheng	2012	N	Sys	N/A	PSO, DS (HJ)	Energy	Chilled water temperatures	HVAC system	?	EnergyPlus
[110]	Li et al	2006	N	Ren	N/A	GA (Matlab GAOT)	Total cost	Plant capacities, Temperatures	CHP system	Meta-model	Matlab
[104]	Lu et al	2005	N	Sys	N/A	GA	Energy	Control parameters	HVAC system	Meta-model (ANFIS)	
[46]	Mahdavi & Mahattanatawe	2003	N	Env	Comm	DS (HC), SA	Visual, Comfort, Energy	Shape, Shading	Envelope	Transient heat balance, Hybrid radiosity & ray tracing	SEMPER
[73]	Manzan & Pinto	2009	N	Env	Comm	GA (MOGA-II)	Energy	Shading	Envelope	Annual hourly , Ray tracing	ESPr, Radiance
[64]	Marks	1997	Y	Env, Form	N/A	DS (Nonlinear)	Construction cost, Operational cost	Shape, Glazing	Envelope	Degree days	CAMOS
[111]	Ooka & Komamura	2009	N	Ren	N/A	GA (MIGA)	CO2, Energy	Plant capacities, Operational strategy	CHP system	Hourly (single day)	
[53]	Palonen et al	2009	Y	Env	Resi	GA (NSGA-II)	Energy, Life cycle cost	Constructions, Heat recovery	Envelope	?	GenOpt, IDA ICE
[84]	Park et al	2003	WS	Env	Comm	DS (Nonlinear)	Daylight	Louver angle	Envelope	Ray tracing (interpolated)	Radiance
[84]	Park et al	2004	WS	Env	Comm	DS (Nonlinear)	Energy, Comfort, Visual	Louver angle, Ventilation	Envelope	Lumped parameter	
[134]	Peippo et al	1999	Y	Env, Form, Ren	Multiple	DS (HJ)	Energy, Total cost	Shape, Glazing, Renewables, Heat recovery, Lighting	Whole building	Annual hourly	
[147]	Pernodet et al	2009	Y	Env, Cont	Retrofit	GA (GenetikSolver)	Energy, Total cost	Constructions, Lighting	Envelope	Meta-model (polynomial)	
[136]	Pountney	2012	Y	Env, Sys, Ren	Comm	GA (SPEA2)	Construction cost, CO2	Constructions, Lighting controls, Systems	Whole building	Compliance methodology	SBEM
[50]	Romero et al	2001	N	Env	N/A	GA, SA	Comfort	Constructions	Envelope	Finite Volume Method , Meta-model (ANN)	
[43]	Sahu et al	2012	N	Env	N/A	GA	Energy	Constructions	Envelope	Admittance method	Matlab
[137]	Salminen et al	2012	Y	Env, Cont	Comm	GA (PA-NSGA-II)	Energy, Construction cost	Constructions, Lighting controls, Ventilation	Whole building	Annual hourly	IDA ICE
[119]	Shaneb et al	2012	N	Ren, Cont	Resi	DS (Linear)	Operational cost	Operational strategy	CHP system	Hourly (single day)	
[116]	Song et al	1999	N	Ren	N/A	Ant Colony	Operational cost	Operational strategy	CHP system	?	
[97]	Stanescu et al	2012	N	Sys	Comm	GA	Energy	HVAC zone grouping	Whole building	Annual hourly	DOE-2
[109]	Tanaka et al	2007	N	Ren	N/A	GA	Energy	Plant capacities, Operational strategy	CHP system	Hourly (single day)	
[71]	Torres & Sakamoto	2007	N	Env, Form	N/A	GA	Daylight	Constructions, Window dimensions, Shading	Envelope	Ray tracing	Radiance
[41]	Tuhus-Dubrow & Krarti	2010	N	Env, Form	Resi	GA	Life cycle cost	Shape, Constructions	Whole building	?	DOE-2
[78]	Turrin et al	2011	N	Form	N/A	GA (Bespoke)	Structural, Solar, Daylight	Shape (via Generative Components)	Structure, Envelope	FEA, ?	STAAD.Pro, EcoTect
[117]	Vasebi et al	2007	N	Ren	N/A	Harmony Search	Operational cost	Operational strategy	CHP system	?	
[139]	Verbeeck & Hens	2007	Y	Env, Ren	Resi	GA	Life cycle cost , Energy , Life cycle EI	Constructions, Ventilation, Renewables	Whole building	Annual hourly	TRN-SYS, COMIS
[132]	Vetterli & Benz	2012	N	Sys	N/A	DS (Mixed integer linear)	Total cost	Plant capacities	Typical zone	Lumped parameter	
[98]	Wang & Jin	2000	WS	Sys	N/A	GA	Energy, Comfort	Set points	HVAC system	Hourly (4 days)	TRN-SYS
[45]	Wang et al	2003	WS	Env, Form	N/A	GA	Life cycle cost , Life cycle EI	Shape, Constructions	Envelope	Hourly (2 days per month)	ASHRAE Toolkit
[51]	Wang et al	2005	Y	Env, Form	N/A	GA	Life cycle cost , Life cycle EI	Shape, Constructions	Envelope	Hourly (2 days per month)	ASHRAE Toolkit
[18]	Wang et al	2006	Y	Form	N/A	GA	Life cycle cost , Life cycle EI	Shape	Envelope	?	
[74]	Wetter & Polak	2005	N	Form	N/A	DS (CS; HJ)	Energy	Window dimensions, Shading	Envelope	Adaptive-precision DAE	BuildOpt
[160]	Wetter & Wright	2004	N	Form	N/A	DS (CS; HJ), PSO, PSO-HJ, GA, DS	Energy	Window dimensions, Shading, Set points	Envelope	Annual hourly	EnergyPlus
[171]	Wright & Alajmi	2005	N	Form	N/A	GA	Energy	Window dimensions, Shading, Set points	Whole building	Annual hourly	EnergyPlus
[92]	Wright & Farmani	2001	N	Env, Sys, Cont	N/A	GA	Operational cost	Constructions, Systems, Set points, Flow rates	Typical zone	Lumped parameter (3 design days)	
[76]	Wright & Mourshed	2009	N	Form	N/A	GA	Energy	Window placement on grid	Whole building	Annual hourly	EnergyPlus
[96]	Wright & Zhang	2005	N	Sys	N/A	GA	Energy	System configuration	HVAC system	Steady-state	
[90]	Wright et al	2002	Y	Sys, Cont	N/A	GA	Operational cost, Comfort	Flow rates, System properties	HVAC system	Annual hourly	
[94]	Wright et al	2008	N			GA	Energy	System configuration, Operation strategy	HVAC system	Steady-state	
[55]	Zemella et al	2011	Y	Env, Form	N/A	Evolutionary neural network	CO2, Energy	Glazing, Shading	Typical zone	Annual hourly	EnergyPlus
[99]	Zhou et al	2003	N	Cont	N/A	DS (Nelder-Mead), SA, GA	Energy	Set points	Whole building	Hourly (peak days)	EnergyPlus
[72]	Znouda et al	2007	N	Env, Form	N/A	GA (Simple)	Energy, Total cost	Shape, Constructions, Shading	Whole building	Degree-hours	CHEOPS

Fig. 1. Summary of all works focussed on optimisation and sustainable building design.

$$G(x_1,x_2,\ldots,x_n) \geq 0$$
$$x_i \in S_i$$

There are a number of objective functions F, which by convention are to be minimised. There are a number of functional constraints G, which by convention must be greater than or equal to zero. Each design variable x_i is constrained to certain values S_i, defined either as discrete values or by boundary values. Objectives and constraints may be interchangeable, depending on how the problem is formulated. Note that in this description there is no requirement for any of the functions to be continuous, or for differentials to exist.

2.2. Multi-objective optimisation

If there is only one objective function, the problem stated above is clear. However, engineering designs frequently require the resolution of conflicting objectives, and there are two common means of achieving this. In a weighted-sum approach, the various objectives are combined to form a single objective, which is then optimised in the normal way. Alternatively in true multi-objective optimisation, also called Pareto optimisation, a range of solutions are sought that span the trade-off between each objective. This trade-off front, also called the Pareto front, is defined based on the concept of *dominance*. This is illustrated for a two-objective minimisation problem in Fig. 2: the highlighted solution is *non-dominated* since there are no solutions in the shaded area. The yellow triangles are all non-dominated and thus make up the Pareto front. All the blue dots are dominated (since there are solutions that are better in both objectives) and thus are not on the Pareto front.

Multi-objective optimisation has developed into a significant research field. Major works include [19–22]. In Fig. 1, under the multi-objective column (MO) each work is labelled as single objective (N), multi-objective (Y) or weighted-sum (WS).

2.3. Algorithms

There are many different methods of using computers to optimise engineering designs. Fig. 3 (after Roy et al., [15]) details many of the methods, and indicates the optimisation characteristics that each is most suited to. (This is not exhaustive, and some algorithms have capabilities that are not highlighted). Brief details are given below of some common optimisation algorithms used for sustainable building optimisation. All are heuristic methods: they do not guarantee to arrive at the true optimum, but offer an efficient method that has a high probability of finding the optimum or of getting close to it. References are given either to the work that proposed them or to a more recent discussion of their use.

'Direct search' covers methods that compare trial solutions with the best found so far, with a strategy based on results so far for determining the next trial. A thorough discussion is given in [23]. Generally these methods are efficient but can get trapped in local optima. Examples used in building optimisation include:

- Pattern search, e.g. Hooke and Jeeves [24]: each dimension in turn is trialled; when no further improvement is possible, the step size is halved.

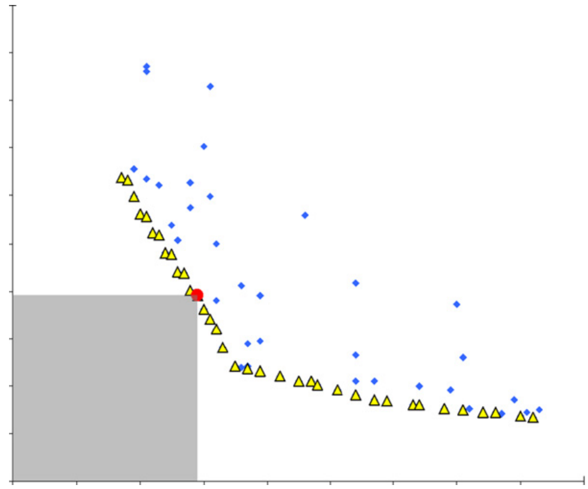

Fig. 2. Pareto front (triangles) and dominated solutions (dots).

- Linear programming, including the simplex method/Nelder and Mead [25]: if the objective function and all constraints are linear, the optimum must fall on an extremal point.
- Non-linear programming: a range of extensions to allow non-linear objectives and constraints (e.g. the interior point method, which traverses a feasible region defined by barrier functions).

Evolutionary algorithms are a common meta-heuristic optimisation algorithm. They apply the Darwinian principle of survival of the fittest by maintaining a population of solutions of which the poorest are eliminated each generation. Common 'operators' applied to generate new solutions include mutation (introducing random changes) and crossover (switching elements from different solutions). Types of evolutionary algorithm include:

- Genetic Algorithms (GA) [17]: a fixed, linear data structure (i.e. a list of variable values). The most common implementation for multi-objective problems is NSGA-II [26].
- Evolutionary Programming (EP) [27] and Genetic Programming (GP) [28]: tree-structures that allow hierarchical variables or representations of functions and programs. In EP only variable values change; in GP the structure also changes.
- Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) [29]: new variable values are sampled from probability distributions, in which the dependencies are represented by a covariance matrix, updated each generation.
- Differential Evolution (DE) [30]: variable values are perturbed by introducing components of other good solutions.

Meta-heuristic algorithms that mimic other natural processes include:

- Harmony Search (HS) [31]: variable values are recombined to find better combinations, with some perturbation to neighbouring values. A rolling population of best solutions is maintained.
- Particle Swarm Optimisation (PSO) [32]: solutions move in design space based on their own position and that of the best position in the swarm.
- Ant Colony Optimisation (ACO) [33]: mimicking the process by which ants deposit pheromones on paths to encourage other ants to follow, variable values that are much-used accumulate 'pheromones' biasing their selection in future choices.

	Complexity			Userinput		Real world		
	Constrained	Multi- Modal	Multi- Objective	Interactive	Qualitative	Robustness	Uncertainty	Reliability
Lagrange Multiplier	✓							
Gradient Projection	✓							
Reduced Gradient	✓							
Feasible Direction	✓							
Direct / Pattern Search	✓							
Leap-frog / Penalty Function	✓							
Linearised Search	✓							
Clonal Selection	✓							
Coevolutionary	✓							
Evolutionary Computing	✓	✓	✓	✓	✓	✓	✓	✓
Swarm Intelligence	✓	✓	✓					
Simulated Annealing	✓	✓	✓					
Immunity -based		✓	✓					
Random Search		✓				✓		
Goal Programming			✓					
Heuristic			✓					
Tabu Search			✓					
Fuzzy Arithmetic			✓	✓				
Mathematical Programming				✓		✓		
Evidence Theory					✓			
Deterministic						✓	✓	
Sequential Approximate							✓	
Discrete								✓
Inverse Reliability Strategy								✓

Fig. 3. Attributes of algorithmic methods (after Roy et al. [15]).

- Simulated Annealing (SA) [34]: solutions are perturbed away from their current positions, and the probability of retaining the better solution is gradually increased with time.

3. Building envelope

3.1. Constructions

The facade of a building forms a barrier to heat, light and air, and so must be carefully designed in order to achieve high performance. Much of this concerns the selection of materials: insulation, glazing etc. Constructions are a straightforward area to optimise as materials can be switched for others from a database without encountering conflicts. Thirty-four of the 74 works in Fig. 1 included variables related to constructions. This section covers works that focus on constructions (although some include basic shape variables like aspect ratio and orientation); the following section covers works predominantly concerned with shape (although some include construction variables as well). Glazing area has been grouped with construction variables, as it

has more in common with properties like insulation than with building form.

Early works in this area used direct search methods and simple simulations. Bouchlaghem and Letherman [35] applied the simplex method and the non-random complex method to minimise discomfort level by varying fabric properties. Al-Homoud [36] optimised energy consumption using the both simplex method and non-linear programming. The variables were concerned with fabric properties as well as shape and orientation. Later works by Al-Homoud [37,38] used the Nelder–Mead method to minimise energy use by varying fabric properties. The former addressed several standard building types; the latter looked at buildings with intermittent occupancy. The admittance procedure was used in all these works to find internal temperatures. It has limitations regarding multi-day performance: it only addresses dynamic effects over a single day. It is quick to execute (and was therefore used when computational resources were more limited), but lacks the detail of modern dynamic simulation programs.

Leskovar and Premrov [39] minimised energy use by varying glazing area using brute-force search, based on a dynamic thermal model in the Passive House Planning Package (PHPP). This simulation program incorporates dynamic effects, and though limited to domestic buildings and specific boundary conditions, this performed well in comparison with more advanced programs. The brute-force search method, however, is very computationally expensive, and so limits the number and resolution of variables.

Such problems are more commonly solved with meta-heuristic algorithms. Coley and Schukat [40] used a Genetic Algorithm to minimise energy use; they varied thermal conductance and thermal capacity for each zone in a lumped parameter model. The novelty of this work was the combination of a GA with human judgements: ‘architectural appeal’ was assessed post-optimisation through the presentation of both optimal and near-optimal designs in a visual manner, enabling the user to choose based on preferences that need not be formalised as constraints or objectives.

Tuhus-Dubrow and Krarti [41] optimised nine construction and two shape parameters of a residential building to minimise life-cycle cost. They used a Genetic Algorithm, based on a previous work [42] in which they compared GA, PSO and sequential search and found GA to be best when more than 10 parameters are to be optimised. Sahu et al. [43] minimised energy use with a GA by varying construction selection for an air-conditioned building in a tropical climate using the admittance method.

In order to address several objectives, Holst [44] used a weighted-sum approach to minimise energy use and the comfort metric Percentage of People Dissatisfied (PPD) using the Hooke–Jeeves method. The variables were window areas and types and thermal properties, and the work used an annual hourly simulation in EnergyPlus. Similarly Wang et al. [45] combined life-cycle cost and life-cycle environmental impact, which was based on construction and operational exergy, varying constructions and glazing areas as well as aspect ratio and orientation. This work used a novel structured Genetic Algorithm that allowed hierarchical variables to be used to avoid infeasible combinations. As detailed in [45], the principal disadvantage of weighted-sum approaches is that only one solution is obtained (for each weight-set) from an optimisation.

Novel approaches to the optimisation of building constructions include the ‘virtual enclosure’ concept optimised by Mahdavi and Mahattanatawe [46]: an abstract description of a building skin based on thermal and visual properties. The advantage of this approach is that multiple actual ‘realisations’ map to a single virtual enclosure, thus allowing the optimisation algorithm to solve only the core underlying problem without conflicting information relating to its realisation. Conversely the downside of this is that subsequent stages are introduced to assign actual design parameters, and discrepancies at this stage may require re-optimisation. The objective was an aggregation of preferences including thermal, visual and energy performance. They compared the optimisation methods of hill-climbing, hill-climbing with a learning evaluation function [47] and simulated annealing; they found that the latter performed poorly.

In one of very few works to address optimisation at the urban scale, Kämpf and Robinson [48] minimised thermal load across an urban area by varying constructions for different groups of buildings. They used a hybrid CMA-ES HDE algorithm, which was developed to help overcome the very large design space of urban optimisation. Solar gains were simulated using CitySim, which deals with resource flows on an urban level. This allowed optimisation of a large area, but compromised on accuracy at the building-level.

Hasan et al. [49] used a hybrid Hooke–Jeeves pattern search and Particle Swarm Optimisation algorithm to minimise life-cycle cost by varying insulation levels, with an annual hourly simulation in the program IDA ICE. Comparison with a brute-force search allowed verification of the results. The focus of the work was on a detached house in Finland: although useful results were generated relating to Finnish building regulations, the lack of other climates or building types limits the relevance of the findings to a very specific sector.

Romero et al. [50] fitted a neural network model to data obtained from a 24-h thermal simulation using the finite volume method. This achieved an increase in speed of 1200 times (for 50,000 evaluations) with an error of less than 10%. This is one of very few works using computational fluid dynamics in an optimisation context, since it requires the use of a meta-model such as the neural network to be practical. They minimised overheating by varying constructions using two optimisation methods, a Genetic Algorithm and simulated annealing.

A multi-objective optimisation in this area was conducted by Wang et al. [51], examining the trade-off between life-cycle cost and life-cycle environmental impact. They used Fonesca and Fleming’s Genetic Algorithm, including structured variables, elitism and mating restrictions, to address the problem previously tackled with a weighted-sum approach [45]. The benefit of the multi-objective approach is clearly demonstrated, with a full Pareto-front of solutions instead of the four obtained using different weight sets.

In an extension of the early direct search methods, Diakaki et al. [52] minimised construction cost and energy consumptions; the variables were wall and window insulation, and the simulation was a steady-state wall conduction model. Compromise programming, goal programming and the global criterion method were applied; all were found to be feasible for simple problems, but that scalability is a serious issue for such methods.

Palonen et al. [53] performed a multi-objective optimisation of energy use and cost using a Genetic Algorithm. The variables were constructions and heat recovery efficiency, and the simulation was performed in IDA ICE (the optimisation was conducted via the GenOpt [54] program). Single and multi-objective formulations were compared, showing the breadth of the multi-objective approach but also the large computational burden.

In a similar approach to [50], Zemella et al. [55] developed a meta-model for facade performance using neural networks. They applied an evolutionary method to generate neural networks that predicted energy use for lighting and cooling, and performed a multi-objective optimisation using this representation. The variables included glazing area, shading configuration and glazing type. The novel Harmony Search algorithm was used by Fesanghary et al. [56] to investigate the trade-off between energy use and life-cycle cost by varying building constructions, though no

specific comparison of its performance was provided. In the often neglected area of humidity control, Huang et al. [57] optimised the location and thickness of moisture-buffering materials using a Genetic Algorithm. The objective functions were humidity level and cost.

Novel non-computational optimisation methods have also been applied in this area. Early work by [58] explored an approach to solar architecture founded in the principles of theoretical physics, which developed thermal balances as a function of mass and exposed surface. An analytical solution by Lucia [59] applied non-equilibrium thermodynamics to the protruding portions of the building envelope to improve internal conditions. In a precursor to the 'virtual enclosure' [46] concept, Sullivan et al. [60] minimised energy use based on the concepts of solar aperture and effective daylight aperture using regression analysis. The process used a database of pre-calculated DOE2 simulations. Bambrook et al. [61] used brute-force search to minimise energy use for a low-carbon dwelling, varying fabric properties and ventilation method. A full annual hourly simulation was performed with IDA ICE. Again, brute-force is shown to be an effective method, but with a very high computational burden (360 simulations for only four coarse variables).

3.2. Form

The form of a building is one of the most contentious areas of design, with architectural, aesthetic, structural and sustainability influences. Regarding sustainable design, form affects solar gains, daylight and fabric heat loss. Unlike constructions, it is often difficult to represent building forms as straightforward parameters. Much work is ongoing in the architectural domain regarding means of generating complex forms in a manner suitable for adjustment and optimisation.

An early work in this area by Gero et al. [62] used brute-force search to optimise cost, thermal load and usable area by vary building shape and glazing properties based on a steady-state thermal calculation. The same group [63], in one of the earliest uses of multi-objective optimisation in building design, also performed a Pareto optimisation using dynamic programming. Objectives included thermal load, daylighting, usable area and cost, and the variables covered massing, orientation and constructions. The example used, the calculation process and the optimisation method were all necessarily simple, but provided an important footing in the concepts of Pareto optimality applied to building design. In particular, comments relating the convexity of the Pareto front to the applicability of rules of thumb is highly insightful. In another similar early works, Marks [64] optimised construction cost and operating cost using non-linear programming. The variables were shape and glazing properties, and the fabric heat loss was calculated based on degree-days.

There have been various analytical approaches to form optimisation. Marsh [65] used an analytical method to optimise the solar envelope based on varying the shade form. Modelling was based on ray-tracing and sun path analysis in EcoTect. The automated generation of shade geometry was shown to work well for simple cases, but was not extended to more complicated arrangements, where a manual analysis-based approach was presented.

Analytical methods have been applied to form optimisation in various ways. Ghisi and Tinker [66] minimised energy use by varying window and room sizes based on an annual hourly simulation using the Visual DOE program. Ordóñez and Modi [67] minimised the combined energy use and embodied energy of a building by varying the number of floors using a steady-state model. Adamski [68] minimised energy use and construction cost by varying building dimensions. These have provided some interesting results, often with greater certainty than meta-heuristic methods. However, in all cases geometric assumptions regarding shape are embedded in the approach used, which limits the wider applicability of the findings.

In the architectural domain, Jo and Gero [69] applied a Genetic Algorithm to a space layout problem, aiming to minimise travel times by allocating activities to different zones. Design schema helped to successfully overcome the complexity of the problems tackled. Caldas and Norford [70] minimised energy use by varying window dimensions using a Genetic Algorithm and an hourly simulation in DOE2. Their method was validated against a simple manual case, and they demonstrated its broader applicability. Torres and Sakamoto [71] optimised daylight availability by means of 21 parameters covering window size, placement, shading and reflectances. They used a Genetic Algorithm to minimise lighting demand based on simulations in Radiance. Their implementation included advanced glare limitation using stochastic control of blinds based on current conditions from a preliminary simulation.

Znouda et al. [72] minimised energy use with a GA by varying shading (average shading factor for winter and summer), and geometry (for a constant floor area), for a degree-hours calculation. The simulation method used is very simplistic, and only one climate was considered (Mediterranean). In contrast, Manzan and Pinto [73] addressed a similar problem, also for a Meditteranean climate, using advanced simulations in ESPr and Radiance. They optimised the depth and angle of a shading device for different glazing options to minimise energy use using the MOGA-II Genetic Algorithm.

Wetter and Polak [74] optimised window and shade sizes using a convergent pattern search algorithm in conjunction with adaptive precision simulations. They used a dramatically different approach, using a set of differential equations to represent the building. The approach is shown to be valid for cost functions that are smooth but approximated in a way that makes them discontinuous, which is typical of building energy problems. The use of varying precision, as controlled by the search algorithm, reduced the computational time by up to a factor of four. The major downside of this approach is that it requires reworking of the simulation programs used to allow the adaptive-precision solving of the underlying equations. This task is currently continuing using the Modelica platform [75].

Novel problem formulations in this area include the discrete grid system used by Wright and Mourshed [76] to optimise the placement of glazing. A Genetic Algorithm was used to minimise energy use based on an hourly annual simulation conducted with EnergyPlus. By discretising the facade into many elements that could be glazed or solid, the size of the design space increased due to many permutations of very small windows. This resulted in interesting but impractical solutions, requiring a constraint to limit the number of windows. This provided more useful results, specifically the bias towards the upper-west corner of the facade.

Kämpf and Robinson [77] varied the location of 11 buildings on a fixed site, each represented by 2D coordinates. They optimised the 'solar potential' of an urban area using the hybrid CMA-ES HDE algorithm along with PPF, a tool based on Radiance. They found their hybrid algorithm to perform better than either CMA-ES or HDE alone on benchmark problems: the CMA-ES aids faster convergence while the HDE adds robustness.

Turrin et al. [78] used a parametric model in Generative Components to optimise a weighted-sum of structural, solar and daylighting objectives. Simulations included Finite Element Analysis using STAAD.Pro and solar and daylight modelling in EcoTect. They explored a number of structural morphologies including multi-layer NURBS systems and domes using Delaunay and Voronoi solutions. The Genetic Algorithm used featured a parallel implementation that included a steady-state population

and half-uniform crossover. They also stressed the importance of parametric design in guiding the thinking of the designer, both by mentally decomposing the problem and visually tracking the progress of the optimisation.

Multi-objective optimisations have been used on various objectives in this area. The trade-off between life-cycle cost and life-cycle environmental impact was investigated by Wang et al. [79] using a Genetic Algorithm to vary the floor shape of a building. Hourly simulation was performed for a typical day per month using the ASHRAE Toolkit. The concept of a schema was used to reduce the complexity of the problem, requiring the number of sides to be predefined. This limits the breadth of the method, and the complexity of the representation for more intricate designs is also acknowledged.

Kämpf et al. [80] simultaneously maximised built volume and solar irradiation (offset by thermal loss) across an urban area. The variables were roof heights and forms, and the simulation was conducted in Radiance. This addressed a similar topic to their earlier work [77], but the multi-objective formulation required a less onerous representation.

In the only work to examine glare issues, Gange and Andersen [81] maximised illuminance and minimised glare using a multi-objective Genetic Algorithm. The process took a 3D massing model as the input along with performance goals, and varied facade element construction, geometry and shading.

Caldas [82] extended her earlier work [70] to include multiple objectives in the GENE_ARCH environment. Abstract (though fixed) form representations were used, called 'shape grammars', for example for an Islamic house typology [83]. This is done in a manner that allows considerable complexity in the underlying form without overloading the optimisation algorithm.

3.3. Double-skin facades

Double-skin facades consist of two glass layers with an air gap, through which ventilation may occur to aid cooling or pre-heating. They are a special case of construction and form optimisation, since they also introduce control and airflow issues.

Park et al. [84] maximised daylighting from a double-skin facade using non-linear programming. The principle was then developed into a real-time optimisation program, first using a lumped model and parameter estimation [85], and later using a Genetic Algorithm [86]. These also addressed temperature and airflow, and considered 10 airflow configurations.

The simultaneous design and control of a double-skin facade was investigated by Evins et al. [87], using a multi-objective Genetic Algorithm to explore the trade-off between heating load and cooling load. Performance was simulated using EnergyPlus combined with the Building Controls Virtual Test Bed [88], which allowed advanced control logic to be implemented. Design variables included placement of openings, flow rate and glazing types; the control variables were temperature set points for activation of different control regimes. The flexibility regarding flow regimes, which were not pre-specified, led to a complex optimisation problem, and also challenges in conveying results clearly.

The optimal performance of double-skin facades has also been optimised via underlying principles rather than computationally by Saelens et al. [89]. This work only considered the three common forms of double-skin facade (passing indoor air through the cavity, passing outdoor air through the cavity, and bringing air in through the cavity).

4. Systems

The Heating, Ventilation and Air Conditioning (HVAC) systems that service building zones can have a significant effect on energy consumption. They require careful configuration and control to operate efficiently. Optimisation of artificial lighting systems is also reviewed.

4.1. Design

Wright et al. [90] conducted a multi-objective optimisation of HVAC system design and control using a Genetic Algorithm. The objectives were energy cost and thermal comfort (Percentage of People Dissatisfied). A single zone and an HVAC system consisting of heat exchanger, heating and cooling coils and fan were simulated hourly for three design days. The zone was simulated using a lumped-capacitance model, and the HVAC system was simulated using a steady-state component model. There were 11 variables relating to HVAC design (coil width, height, number of rows, number of circuits, maximum flow rate; heat recovery fan size) and 189 control variables (supply air temperature and flow rate for 24 h for 3 design days; on/off status for 15 unoccupied hours for 3 days). Constraints were imposed governing coil design, fan performance limitations and system capacity; constraint violations contributed to an infeasibility objective, which quantified the degree of infeasibility for a given solution, and was included as a third objective in the algorithm (see [91]). Results were presented for three different thermal weights for the three design days (summer, winter, swing). This work built upon a previous study by Wright and Farmani [92], which additionally included three fabric properties as variables.

Wright, Zhang and others [93–95] conducted an extensive optimisation work examining the configuration of HVAC components. A Genetic Algorithm was used for the optimisation, and the complexity of the problem required the development of a new 'ageing operator' [96] to enable the algorithm to successfully solve this highly constrained topological problem. The variables included component selections, network topologies, flow rates and thermal capacities. Stanescu et al. [97] also optimised the configuration of an HVAC network by assigning different zones to different systems. HVAC energy use was minimised based on simulations in DOE2. They used a Genetic Algorithm, encoding a list of zone numbers and breaks to denote different systems, and investigated the effect of different genetic operators.

4.2. Control

Wang and Jin [98] minimised the running cost of an HVAC system using dynamic models that were developed to 'self-tune' the system, using parameters optimised by a GA. The system was simulated dynamically in TRN-SYS for changing weather conditions. Users could select different weights for the factors in the objective function, allowing a greater degree of flexibility. This process of on-line parameter estimation is the first step towards 'live' model-based control optimisation (which is beyond the scope of this review).

Zhou et al. [99] compared several optimisation methods for minimising electricity cost by varying cooling set points. The algorithms used were Nelder–Mead, the Broyden–Fletcher–Goldfarb–Shanno (BFGS) method, simulated annealing and a Genetic Algorithm. It was found that the Nelder–Mead method provided the best performance for the problem addressed, but the results were thought likely to be problem-specific. The work was part of an exercise to incorporate an optimisation module into EnergyPlus.

Fong et al. [100] minimised energy use in an HVAC system using evolutionary programming. The variables were chilled water supply temperature and air supply temperature, and the system was simulated dynamically using TRN-SYS. Evolutionary programming was used due to the highly constrained nature

of the problem, and although the method was shown to work, no comparison to other methods was undertaken.

More recent works have modelled HVAC systems by validation against building energy models and measured data. This has a useful role in validation and in control optimisation for systems that are already configured, however the specific nature of the problems addressed make it less generalisable than simulation-based approaches. Lee and Cheng [101] minimised chiller energy consumption in this way by adjusting chilled water temperatures using a hybrid algorithm combining Particle Swarm Optimisation and Hooke–Jeeves. Congradac and Kulic [102] addressed a similar problem using a Genetic Algorithm and a meta-model consisting of a neural network representation trained on measured data. A neural network was also fitted to measured system performance data by Chow et al. [103]. They minimised the operating cost of a chiller using a Genetic Algorithm. The variables were supply and return flow rates and temperatures. In a similar fashion, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was used by Lu et al. [104] to model an HVAC system by fitting to measured data. They then minimised energy use by varying the control parameters using a Genetic Algorithm.

Other works have addressed HVAC control issues without directly incorporating building performance. Huang and Lam [105] optimised a Proportional-Integral-Derivative (PID) controller for an HVAC system using a Genetic Algorithm. The objectives, combined via weighted-sum, were overshoot, settling time and mean squared error from the specified value. The controller was simulated by a dynamic non-linear model using HVACSIM+. Yang and Wang [106] used Particle Swarm Optimisation to conduct a multi-objective optimisation of operating cost and comfort by varying control parameters. The control system was modelled analytically, and they assumed that the building responded directly to external conditions. Whilst these methods may be useful in understanding the details of the systems under consideration, the absence of information regarding building-level performance means they are limited in application.

4.3. Lighting

Artificial lighting in buildings can have significant energy use and contribute to cooling demand or overheating. Works detailed elsewhere have addressed issues of daylight availability [71,78,84] and glare [81]. Many of the works concerned with energy use have simulated daylight availability in order to account for the reduced need for artificial lighting.

The prediction of daylight levels by model-fitting was addressed by Coley and Crabb [107], who used a Genetic Algorithm to find attenuation coefficients to predict internal daylight levels based on data from external sensors. In reality this approach is likely to have been superseded by programs that simulate lighting levels directly without the need for training on measured data.

In the only work to optimise artificial lighting design, Cassol et al. [108] performed a multi-objective optimisation of lighting energy use and lighting level provided by varying light locations and powers. The optimisation method used was Generalized Extremal Optimization, and the simulation used the radiosity method. The optimisation was computationally intensive, but was reported to be robust and flexible.

5. Energy generation

Whilst there is much to be gained by reducing the energy demands of buildings, to achieve very low or zero carbon emissions, energy must be generated renewably to meet those demands which are unavoidable. Many regulatory and assessment systems require the means of generation to be connected directly to the building that they serve. The following sections outline optimisation applications in three areas of building-integrated energy generation.

5.1. Combined Heat and Power

Combined Heat and Power (CHP) systems take advantage of waste heat from electricity generation to provide heat to buildings, both for space heating and hot water provision. Systems range in size from micro-scale, supplying single dwelling, to district heat networks supplying large urban areas. Systems can also incorporate absorption chillers that use available heat to make chilled water for cooling; this is termed Combined Cooling Heat and Power (CCHP).

Tanaka et al. [109] minimised the energy used by a large CHP system using a Genetic Algorithm. They varied the combinations of CHP and boiler plant as well as the start and stop times and the load factors of the CHP. The major limitation is that optimisation was only conducted over a single day instead of over a year.

The Net Present Value of a CHP system was optimised by Li et al. [110] using a GA. The variables were plant combinations and temperatures at points in the system. A meta-model was fitted to manufacturer data and benchmark demand values, which limited the applicability to specific building designs. However, various economic factors, for example the impact of tax incentives, were considered at the macro level.

A two-stage optimisation process was developed by Ooka and Komamura [111] to minimise carbon emissions and energy use in a CCHP system. The first stage addressed equipment capacities, while the second determined hourly output coefficients. They used a multi-island Genetic Algorithm, and demand data was for a peak day for an existing building. Uniquely for this area of optimisation, solutions were validated against brute-force search.

A multi-objective Genetic Algorithm was used by Kayo and Ooka [112] to examine the trade-off between energy use and costs (both capital and operating) of a distributed energy system. This was the logical extension of the previous work to the multi-objective case, and demonstrated the trade-off available between emissions and cost. The variables were capacities for absorption chillers, heat pumps, gas boilers, co-generation systems and a photo-voltaic system. Demands were for a peak day for each season, selected from data for an existing building.

The same trade-off was explored by Evins et al. [113] regarding a CCHP system serving a development constructed in several phases. Plant capacities and thermal store size were varied along with plant construction dates, included to allow the phasing of plant construction to be optimised. Plant operation was simulated hourly over the project lifespan, using an electricity-load-following logic that also sought to minimise plant start-ups. This work is unique in simulating the proposed design both thermally and economically over the whole lifespan of the plant.

Abdollahi and Meratizaman [114] performed a three-objective optimisation of the exergetic efficiency, levelised cost rate and environmental impact of a small-scale CCHP system. They used a Genetic Algorithm, and the variables were the turbine power generation and the absorption chiller load. The system was simulated as a 'thermoenvironomic' model incorporating availability of the plant, and a final solution was selected based on a risk analysis. Demand data was from a steady-state thermal model.

The heat and power dispatch problem addresses the need to meet demands for heat and electricity as efficiently as possible. Part-load states and changes to the heat to electricity ratio both affect plant efficiency, which in turn affects running costs. It

forms a sub-problem to the broader design and management issues addressed in the works above. Guo et al. [115] addressed the dispatch problem analytically using the Lagrangian relaxation technique. Song et al. [116] minimised the operating cost of a Combined Heat and Power (CHP) system using Ant Colony Optimisation. Vasebi et al. [117] also minimised the operating cost of a CHP system by addressing the heat and power dispatch problem using the novel Harmony Search algorithm. An analytical approach was used by Silveira and Tuna [118] to optimise CHP functionality based on a thermo-economic analysis method involving pressures and temperatures. The online optimisation of operating strategy was tackled by Shaneb et al. [119] using linear programming for the control of a micro-CHP for a residential building.

The following works address related areas. Hawkes and Leach [120] investigated the impact of temporal precision on solving the dispatch problem, finding that this could give discrepancies of up to 40% in energy delivered. Dominguez-Munoz et al. [121] examined the selection of typical demand days for CHP optimisation using a partitional clustering process.

5.2. Solar technologies

Solar technologies use energy collected from solar radiation, either to heat hot water or to produce electricity through Photo-Voltaic (PV) cells. These technologies are often integrated into buildings, most commonly roofs, using the structure for support at a high, unobstructed level. Solar thermal systems almost always produce low-grade heat, for which the most significant demand is hot water supply in buildings. PV cells can provide electricity when needed in the building, and export the excess to the grid at other times; this can reduce the need for centralised infrastructure and the corresponding conversion losses of long distance power delivery.

Various problems related to building-integrated solar technologies have been tackled analytically. Charron and Athienitis [122] maximised the efficiency of a double-skin facade system combining vision glazing and PV panels by varying the placement and detailing of the two element types. Khatib et al. [123] optimised the sizing of a hybrid PV/generator system to minimise cost. Milan et al. [124] examined the provision of renewables in residential buildings, including the interdependencies between demand, provision and availability. They considered PV, solar thermal, a heat pump and a storage system. Performance was described analytically, and optimisation was performed using linear programming. Ren et al. [125] minimised the operating cost of a residential building by varying the capacity of a PV array using linear programming. Ghiaus and Jabbour [126] used Design of Experiments to optimise the total cost of a solar collector by varying the area and tank size, based on simulations in TRN-SYS.

Meta-heuristic methods have also been applied. Talebizadeh et al. [127] maximised the energy generated by a PV array by varying the collector angles using a GA. Bornatico et al. [128] investigated the optimal sizing of a solar thermal collector, comparing Particle Swarm Optimisation to a Genetic Algorithm. They used a weighted-sum approach to combine the objectives of solar fraction (maximised), with energy use and construction cost (minimised). The variables were collector area, tank volume and auxiliary power unit size.

5.3. Ground energy and storage systems

Ground temperatures remain roughly constant throughout the year, providing a useful temperature differential (i.e. warmer than the atmosphere in the winter, cooler in the summer). Heat pumps use this difference to provide heat for buildings, via either water or air pipes buried underground. In addition, excess energy (e.g. heat extracted via the cooling system in the summer) can be stored by injecting it into the ground, then extracting it again when needed. Other storage systems, including ice storage and thermal vessels, can be used to reduce peak demands. Below are some examples of the application of optimisation to these technologies.

Kumar et al. [129] used a GA to maximise the cooling potential from an earth-to-air heat exchanger by varying pipe properties and flow rate. Khalajzadeh et al. [130] represented a vertical ground heat exchanger using a meta-model and maximised the heat transfer efficiency by varying pipe diameters, flow velocities and temperatures. De Ridder et al. [131] used dynamic programming to minimise the operating cost of a building that used borehole thermal energy storage by varying control parameters. Vetterli and Benz [132] optimised the capacity of an ice storage system using mixed integer linear programming. They formulated an analytical model of the building, it's thermal capacity, the ice storage and the vapour compression system. Blarke et al. [133] used mixed integer linear programming to optimise the operational strategy of a thermal battery to minimise operational cost. They used benchmark assumptions regarding building performance.

6. Holistic approaches

By splitting building design problems into sub-problems (envelope, systems, renewables), the above works may miss out on synergies between different areas. This is particularly true of multi-objective problems. The following works consider the whole building system holistically by optimising variables from several areas simultaneously.

Peippo et al. [134] optimised a diverse range of variables covering form (aspect ratios, glazing area), constructions (glazing type), renewables (solar thermal collector area, PV array area) and systems (heat recovery, lighting type, lighting controls). A targeted multi-objective optimisation was performed with the objectives energy use and cost (including annualised capital costs). The optimisation was conducted using the Hooke–Jeeves algorithm. Results were presented for a residential and a commercial case study for three different climates; for each case the optimisation was conducted for a minimum cost target, then for a relative (to the minimum cost case) energy use target of 75%, 50% and 0%.

Evins et al. [135] optimised the cost and energy use of a modular building for different climate types. The variables included constructions (*u*-values, shading), HVAC (heating and cooling systems) and renewables (PV, solar thermal). Shading was optimised using a local search, which was embedded in the Genetic Algorithm used for all other variables.

Pountney et al. [136] compared a Genetic Algorithm to a Marginal Abatement Cost (MAC) curve approach for buildings modelled with SBEM. The optimisation problem examined the trade-off between carbon abatement and cost, and the variables were insulation values, air tightness, lighting controls, system efficiencies and PV provision. This is a sound approach, but the specific findings are limited to optimisation for compliance with building regulations.

Salminen et al. [137] conducted a multi-objective optimisation of cost against improvement over the LEED baseline. This used a full LEED energy simulation in IDA-ICE, which meant large computation times and thus fewer solutions. The suggestion is made that a simpler model could be used in the early stages of optimisation to combat this. They used Pareto-archive NSGA-II, and the variables covered insulation values, lighting controls and night ventilation times. Although variables from different areas of design were considered, too many factors were already fixed for the optimisation to greatly reduce the energy consumption.

6.1. Residential buildings

Domestic buildings usually present a more straight-forward design problem than more complicated building types. Limiting investigations to dwellings offer the opportunity to conduct holistic optimisations that cover a greater proportion of the significant parameters. In this area, several works have optimised different groups of properties in separate stages. Bichiou and Krarti [138] performed a single-objective optimisation of life-cycle cost for residential buildings, varying the envelope and HVAC system. They compared the robustness and effectiveness of a Genetic Algorithm, particle swarm optimisation and sequential search, finding that the latter performed poorly in terms of computational effort. They also compared the holistic approach with optimising the envelope first then the systems separately: the former was slightly more effective but slightly slower.

A multi-objective optimisation of the energy use, ecological impact and cost of dwellings was conducted by Verbeeck and Hens [139]. They used a two-stage process, first optimising envelope properties including constructions, shading, glazing area and air tightness, then second optimising system properties including CHP, heat pumps, storage and controls. Energy simulations were done in TRN-SYS with natural ventilation rates calculated in COMIS. The scope was further broadened by a discussion of the balance between embodied energy and operational energy, and between capital and running costs. They also conducted an extensive uncertainty and perturbation analysis to identify sensitive parameters, similar to that of Evins et al. [113].

Evins et al. [140] optimised all highly significant variables of a residential building based on UK Building Regulations compliance. A framework was applied that included design-of-experiments to screen the significant variables (from a total of 103), an initial coarse optimisation (21 variables) and a detailed optimisation (14 variables). The optimisation stages used NSGA-II; the objectives were costs and carbon emissions. Costs included construction and operation costs offset by income from Feed In Tariffs; future payments and incomes were discounted using the Net Present Value method. Carbon emissions were calculated using the Standard Assessment Procedure (SAP). Similar to Pountney et al. [136], the use of a compliance tool for optimisation gives greater freedom but also limits the applicability to a particular regulatory framework.

Hamdy et al. [141] optimised eight variables relating to insulation, glazing, shading, heat recovery and system choice. The trade-off between carbon emissions and investment cost was investigated for three different overheating constraints, and the results compared. Simulation was with IDA ICE. The optimisation method was a GA with two modifications: a deterministic solver was used to obtain the initial population, and a multi-objective goal attainment algorithm was used to refine solutions with high diversity. They investigated [142] the impact of adaptive thermal comfort criteria by conducting separate optimisations for different comfort levels. They also developed a multi-stage approach [143] to find cost-optimal near-zero energy domestic buildings under the Energy Performance of Buildings Directive (EPBD). The EPBD contains guidance on a matrix of combinations of design measures, which was taken as the basis for the optimisation problem. A multi-objective Genetic Algorithm was applied to the problem in three stages: envelope, systems, renewables. This helped to reduce the computational load and increase the transparency of the solutions.

Brute-force search has also been applied to holistic approaches. Achten et al. [144] used it to investigate the effect of a wide range of energy saving measures on domestic buildings for both new-build and retrofit cases. The results were analysed to find the Pareto trade-off front between cost (net present value) and energy use. There were 35,720 variations of envelope and 13,720 variations of systems, meaning each had to be addressed separately. This is a limitation on the holistic benefits of the approach, which was only possible in this context due to the simplified simulation used.

Griego et al. [145] used brute-force search to explore the trade-off between running costs and energy use for a residential building in Mexico. The variables included fabric properties, air tightness, internal loads and renewables provision. The interactions between measures was investigated, which is one advantage of the brute-force approach due to the large amount of data available. This could have been taken further through the use of data mining processes.

An analytical approach was taken by Uctug and Yukseltan [146] to optimise glazing, lighting, appliances and PV. In a reverse of the typical cost-minimisation formulation, they used linear programming to examined efficient budget allocation to maximise energy savings for a residential building in Turkey.

6.2. Retrofit

Retrofitting or renovating existing buildings introduces design challenges beyond those found in new construction. Retrofit options for schools in France were optimised by Pernodet et al. [147] to meet stated energy targets as cheaply as possible. The optimisation used a Genetic Algorithm and a polynomial-based meta-model that was fitted to results from dynamic thermal simulations. The variables covered constructions, lighting power and controls. This is an early work in the area of retrofit optimisation, and suggests many possible improvements found in later works.

There are two examples of three-objective optimisation in this area. Chantrelle et al. [148] analysed renovation options to optimise cost, energy use and comfort by varying constructions and control options. The optimisation was performed using a Genetic Algorithm and the simulation was with TRN-SYS and COMIS. The increase in computational requirements of using three objectives were not explicitly assessed, but were state to be not excessive.

A similar problem was tackled by Jin and Overend [149], examining the trade-off between cost, energy use and user productivity for a retrofit project looking at improvements to envelope and systems. The user productivity metric was quantified using indicators relating thermal, aural, visual and air quality factors [150]. One difference from [148] lies in the use of distinct ‘renovation strategies’ rather than individual components: whilst this is narrower in scope, it is well-aligned with the retrofit application. Another notable feature of [149] is the use of three 2D projections to aid interpretation of the 3D Pareto plot.

Asadi et al. [151] used an analytical approach to examine the trade-off between cost and energy use for retrofit options relating to the building envelope and solar thermal system. Due to the combinatorial nature of the problem and the analytical formulation used they were able to apply Tchebycheff programming. This varies the weights applied to objectives to generate a Pareto set of solutions from a direct optimisation method. Whilst their approach is extendible to a resistance–capacitance thermal model, it is not applicable to simulation-based optimisation.

7. The optimisation process

7.1. Process

Various platforms have been developed to assist in sustainable building optimisation. GenOpt, by Wetter [54], allows interchangeable simulation engines and optimisation algorithms to be connected. ArDot, by Mourshed et al. [152], has a similar function; they discuss the role of optimisation in the design

process, and the formulation of building optimisation problems. Frameworks have also been proposed to guide the optimisation process. Wang et al. [18] developed an object-oriented framework for green building optimisation, supporting hierarchical variables and different simulation engines. Bleiberg and Shaviv [153] used optimisation to build a collaborative design framework. They used a Genetic Algorithm to better understand the interactions of design parameters from different areas of the design process, in order to control conflicting priorities. Geyer [154] presented a component-oriented framework to facilitate multi-disciplinary design optimisation. Evins et al. [140] developed a framework that applied design-of-experiments to find significant variables, followed by coarse and detailed optimisation stages.

Other works have looked at how to best establish the goals of an optimisation process. Analytical Target Cascading was applied to building energy performance analysis by Choudhary et al. [155] to generate holistic performance goals. This hierarchical process links different goals mathematically and uses a top–down and bottom–up iterative approach to derive the best overall set of compatible goals. Their subsequent paper [156] applied this to a case study and examined the implications for simulation-based systems. Ochoa et al. [157] examined the impact of different visual and energy performance metrics on optimisations involving glazing.

The outputs from multi-objective optimisations are often hard to interpret, involving complex interactions in design- and objective-space. Brownlee and Wright [158] investigated methods of analysing the solutions obtained from a multi-objective optimisation. They developed a method of ordering solutions by one objective and examining the correlations between design variables. Evins et al. [159] addressed visual methods of presenting and exploring data from building performance simulations, including multi-objective optimisation. Case studies were presented examining the use on live projects of techniques including interactivity and animation of data.

7.2. Algorithms

Many single-objective algorithms were compared by Wetter and Wright [160]: coordinate search and Hooke–Jeeves (forms of direct search), Particle Swarm Optimisation (PSO), PSO with mesh, combined PSO-HJ, a Genetic Algorithm, mathematical programming using Nedler–Mead, and the gradient-based Armijo algorithm using finite difference approximations. They found that discontinuities in the objective function caused by approximation issues with the EnergyPlus solver led to failure for algorithms that require smoothness. The best solutions were found using the PSO-HJ hybrid, but the GA performed nearly as well and needed fewer simulations. Wetter went on to develop BuildOpt [161], based on solving differential equations with adaptive precision coupled with pattern search algorithms. By using a means of simulating building performance that is smooth and differentiable in the design parameters, he bypassed the need for 'black box' optimisation methods.

Brownlee et al. [162] compared the performance of five multi-objective algorithms (IBEA, MOCell, NSGA-II, SPEA2 and PAES) along with random search in solving a multi-objective problem concerning window placement; NSGA-II was found to perform best. Bichiou and Krarti [138] compared a Genetic Algorithm with PSO and sequential search; this built upon a similar study by Tuhus–Dubrow and Krarti [42], both finding that GA performed best, especially for problems with more than 10 variables.

Kämpf et al. [77] developed a hybrid of the CMA-ES and HDE algorithms in which the population from the former feeds into the latter in a series-loop, allowing CMA-ES to perform a quick sweep of the search space and HDE to home in on the exact solution. They demonstrated that for two test functions and an application involving solar potential their hybrid performed better overall than either algorithm alone.

Wright and Loosemore [91] developed an 'infeasibility objective', a new method of constraint handling for multi-objective optimisation. By combining many constraints into a single objective, they improved the dimensionality of the problem and the transparency of the solutions. Angelov et al. [163] developed new operators for topology optimisations: a 'link' mutation that switches connections in a network, and a 'position' mutation that switches components. Wright and Zhang [96] developed an 'ageing operator' that penalised highly dominant solutions to aid in solving highly constrained problems. Evins et al. [164] investigated the configuration of a Genetic Algorithm for optimisation of solar gain, looking at population size, number of generations, crossover and mutation probabilities, selection method and seeding method. Hamdy et al. [165] used a single-objective preparation step and a post-optimisation refining step to improve upon the performance of a Genetic Algorithm. They applied these steps to an example problem, and found benefits in terms of accuracy and optimisation speed. They later [166] examined the use of passive and active Pareto archiving with the NSGA-II algorithm in cases where long run times allow only a very low number of solution evaluations.

Meta-models may be used to allow optimisation algorithms to perform many objective function evaluations without running full simulations each time. Siddharth et al. [167] used a Genetic Algorithm to fit a non-linear regression model to predict energy use and zone temperature based on insulation, lighting and system parameters. The fitted model was then used to find optimal designs in conjunction with a cost function. Eisenhower et al. [168] developed a methodology for the use of meta-models in building optimisation. They fitted a Support Vector Machine meta-model to a design problem with over 1000 parameters, and optimised thermal comfort and energy use with an interior-point algorithm that used the derivatives available from the meta-model. In a subsequent work [169] this was extended to include uncertainty weightings in the meta-model. Tresidder et al. [170] fitted a Kriging meta-model to simulation results, which was then optimised using a Genetic Algorithm. They compared using Kriging with querying the simulation directly, and found that for single-objective optimisation it offered an advantage, and for multi-objective optimisation it was advantageous if a limited number of simulations were possible.

Uncertainty and sensitivity to inputs is a concern in all areas of building simulation, and has been investigated in relation to optimisation. Wright and Alajmi [171] examined the robustness of Genetic Algorithms in solving building optimisation problems, and concluded that the method is reasonably robust to both control parameters and the random processes of chance. Hopfe et al. [172] investigated the propagation of uncertainty through a building design optimisation algorithm to aid robustness. A Kriging meta-model was used to allow many simulations, permitting variations of uncertain parameters to be explored via perturbation with a Monte Carlo sampling. Wright et al. [173] used multi-objective optimisation solutions to perform a global sensitivity analysis. They concluded that using either initial or all solutions from the optimisation allows variable importance to be determined, but that convergence of variables was not related to their importance.

8. Trends

Fig. 4 presents graphical information on the works included in the main summary (Fig. 1). Note that since some works covered several methods or objectives, the total number of works is not the same in all graphs.

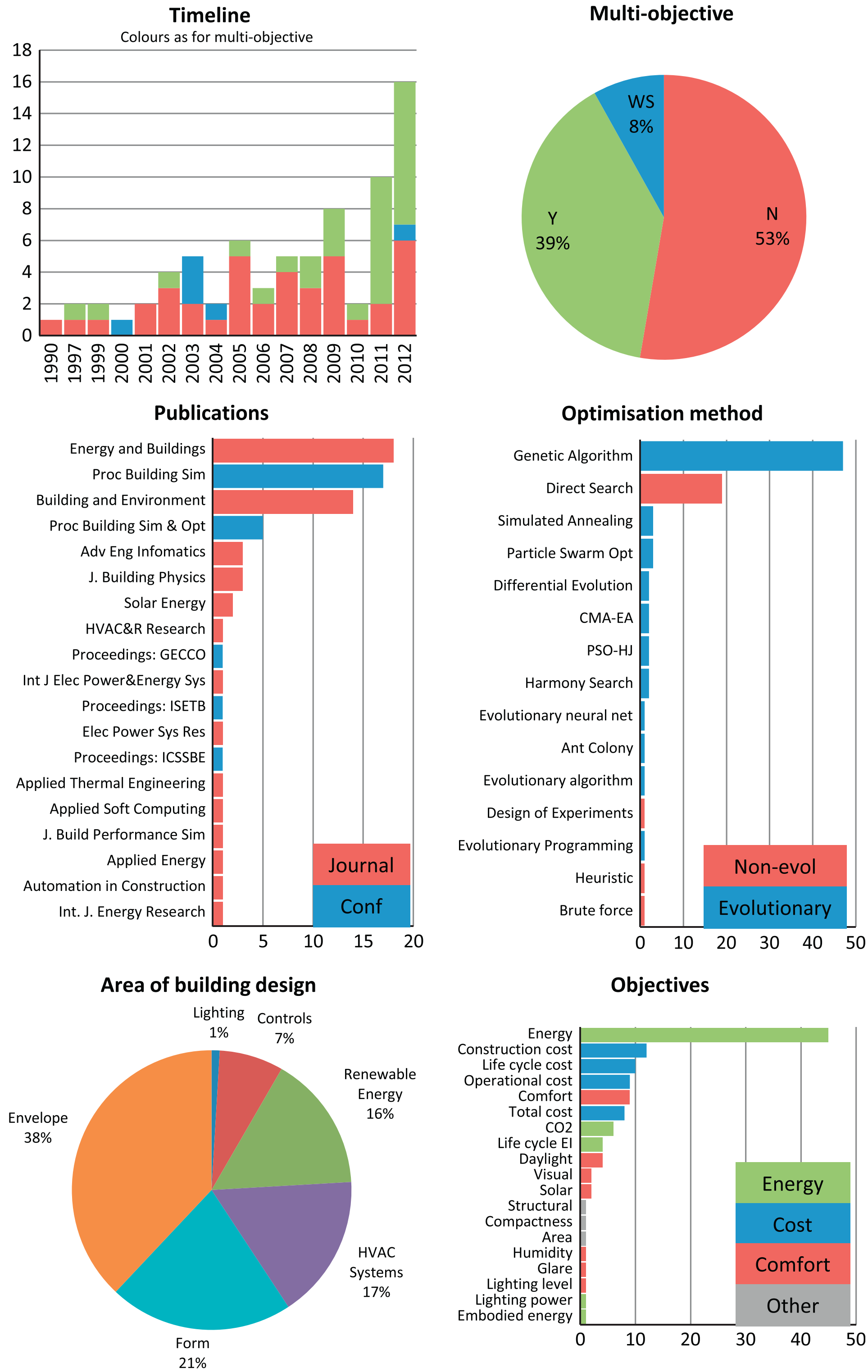

Fig. 4. Graphical summary of the works in Fig. 1.

There has been a notable increase in works featuring optimisation of buildings over the last decade, from a handful per year to 16 in the current year to date. Around half of the works addressed single objective problems. This formulation is straight-forward and allows detailed exploration, for example by including more variables. A small number of works extended the single-objective formulation by using a weighted-sum of different objectives. Around 40% of works applied full Pareto multi-objective optimisation. This is becoming much more common, with more than half of these cases in the last two years. The two works that performed a full 3-objective optimisation [148,149] were also in this period.

The majority of works (more than 70%) were published in journals focussed on building energy issues (Energy and Buildings, Building and Environment) or in conferences focussed on building energy simulation (Building Simulation, Building

Simulation and Optimisation). Other publication options included broader energy or building-related journals, engineering journals, and computational optimisation journals and conferences.

The most common optimisation method was a Genetic Algorithm, used in more than half the works. Direct search methods were also popular, used in a quarter of cases. Other evolutionary algorithms accounted for almost all of the remainder. Particle Swarm Optimisation, especially when combined with Hooke–Jeeves,

The single most common objective was energy use, used in 60% of cases. There were several variations (construction, operational, life-cycle, total) on cost objectives, which together were present in nearly as many cases. The other common set of objectives related to comfort, with several metrics were used including many related to daylight levels. If the works are categories by predominant area of building design, envelope occurred most frequently, in nearly 40% of works. Form, systems and renewables each accounted for around 20% of works, with controls and lighting occurring in very few cases.

9. Conclusions

This section draws upon the evidence presented to speculate about future trends and challenges in computational optimisation of sustainable buildings. There is clear growth in the popularity of optimisation for sustainable building design, and of multi-objective optimisation in particular. This is partly due to the ever-increasing computational power available to address problems that were previously infeasible. This is likely to continue, with optimisation expanding into areas currently beyond our capabilities. This may include Computational Fluid Dynamics (CFD), where long run-times currently preclude the use of optimisation. Another area is form optimisation, where advanced representations and many evaluations are needed to explore the very large design space. Holistic optimisations of many areas of building design will also increase, covering many detailed variables or bringing together different fields of building design.

The commercial application of optimisation on live projects requires time, knowledge and resources that until recently have been unavailable outside academia. As the computational capacity available to companies expands, perhaps through cloud computing, optimisation will be used more often. Another reason for the increasing interest in optimisation is that industry is realising the great potential of such methods. They are facing more stringent challenges than ever, with an increased need for designs to perform environmentally and economically. Design requirements are starting to mandate actual energy use, for example ratings for Display Energy Certificates (DECs) that the building must achieve in use. This will require optimisation methods to better account for uncertainty and robustness. Optimisation is already being incorporated into building simulation packages, and progress in terms of the interoperability of software packages and environments will continue this trend. Holistic optimisations have shown the benefits of addressing design issues in harmony rather than disparately. Through the growth of Building Information Management (BIM) processes, all aspects of building design will become more integrated, include simulations, assessment methods and design aids. Applying optimisation tools and extracting useful information from the results will be a key part of this at all project stages.

The works presented demonstrate the breadth of approaches that can be taken. Phrasing of the optimisation problem is key, in terms of scale and complexity as well as scope. Holistic optimisations offer many benefits. In order to challenge conventional wisdom and provide real benefit, problems must be broad enough to allow exploration without being unsolvable. It is also notable that as the scope of problems expands in breadth and depth, making sense of the results becomes more important. It is likely that further work on this aspect of the problem will be needed. Optimisation is a process, rather than a technique or a method, and this provides perhaps the greatest challenge: how to assist designers in applying the process to best effect.

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